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# MACHINE LEARNING–BASED EARLY PREDICTION OF SEVERE PREECLAMPSIA USING ELECTRONIC MATERNAL HEALTH RECORDS IN PAKISTAN

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## Abstract

*Preeclampsia is a major pregnancy-related complication that can rapidly progress to severe maternal and fetal outcomes, particularly where timely risk identification and referral are limited. This study examined the potential of machine learning (ML) to predict severe preeclampsia using routinely available electronic maternal health records in Pakistan. A retrospective quantitative design was proposed using demographic, obstetric, clinical, and laboratory variables, including maternal age, BMI, previous preeclampsia, hypertension, diabetes, gestational age, and blood-pressure measurements. A dataset of 1,000 maternal records was used to demonstrate model development and evaluation. Logistic Regression, Random Forest, Support Vector Machine, and XGBoost were compared using AUC, accuracy, sensitivity, specificity, and F1-score. In the analysis, XGBoost achieved the highest predictive performance (AUC = 0.91), followed by Random Forest (AUC = 0.89), SVM (AUC = 0.86), and Logistic Regression (AUC = 0.82). Blood pressure, previous preeclampsia, BMI, chronic hypertension, and diabetes emerged as important predictors. The findings suggest that ML may support early risk stratification and clinical decision-making for severe preeclampsia. However, the reported results are based on synthetic data; therefore, they do not represent actual clinical outcomes from Pakistani patients. Future research should validate the proposed framework using large, multicenter Pakistani datasets and prospective clinical studies.*

## 1. INTRODUCTION

Preeclampsia is a multisystem hypertensive disorder of pregnancy and remains a major cause of maternal and perinatal morbidity and mortality worldwide. It generally develops after 20 weeks of gestation and may involve hypertension accompanied by proteinuria or other manifestations of maternal organ dysfunction. Severe disease can progress rapidly to neurological, renal, hepatic, hematological, and cardiovascular complications, as well as fetal growth restriction, preterm birth, and stillbirth. The heterogeneous clinical presentation and unpredictable progression of preeclampsia make early identification of women at high risk particularly important (Ali et al., 2024; Phipps et al., 2019).

The global burden of preeclampsia remains considerable, with recent evidence demonstrating substantial geographical variation in prevalence and outcomes. Vera-Ponce et al. (2025), in a systematic review and meta-analysis, reported considerable worldwide variation in the

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prevalence of preeclampsia and related hypertensive disorders. This variation is particularly relevant to low- and middle-income countries, where limited access to antenatal care, delayed referral, inadequate diagnostic facilities, and shortages of specialized maternal healthcare may increase the consequences of undetected disease.

Pakistan represents an important context for investigating improved approaches to maternal risk prediction. The country's healthcare system is characterized by substantial variation in access to antenatal services, quality of care, health information systems, and specialist obstetric services. Evidence from the Community-Level Interventions for Pre-eclampsia (CLIP) trials conducted in Pakistan and other low-resource settings demonstrated the importance of timely recognition, triage, referral, and treatment of women at risk of severe maternal complications (von Dadelszen et al., 2020). Consequently, an accurate early-warning mechanism could potentially strengthen existing maternal surveillance and referral systems.

Traditional prediction of preeclampsia relies on established clinical risk factors such as maternal age, parity, previous preeclampsia, chronic hypertension, diabetes, obesity, and family history. These factors are clinically meaningful, but their predictive value may be limited when evaluated independently. Preeclampsia results from complex interactions involving abnormal placentation, endothelial dysfunction, angiogenic imbalance, inflammation, oxidative stress, and maternal metabolic and cardiovascular susceptibility (Phipps et al., 2019). Such complexity creates an opportunity for computational approaches capable of modelling nonlinear relationships and interactions among multiple predictors.

Electronic health records (EHRs) provide an increasingly valuable source of longitudinal maternal information. Routine antenatal records may contain demographic characteristics, obstetric history, repeated blood-pressure measurements, BMI, comorbidities, laboratory investigations, medication information, and pregnancy outcomes. Unlike conventional risk scores based on a small number of predetermined characteristics, EHR-based predictive models can integrate multiple dimensions of maternal health and potentially identify subtle patterns preceding clinical deterioration.

Machine learning (ML) has consequently gained increasing attention as a method for pregnancy-risk prediction. ML algorithms can identify complex nonlinear relationships and interactions within high-dimensional clinical data without requiring all relationships to be specified in advance. Random Forest, Support Vector Machine, Logistic Regression, gradient-boosting algorithms, and neural-network approaches have been investigated for preeclampsia prediction. A systematic review by Ranjbar et al. (2024) reported promising discriminatory performance across ML models, although the authors emphasized limitations involving study heterogeneity, methodological quality, and external validation.

Evidence from routinely collected clinical data is particularly relevant to resource-constrained settings. Tiruneh et al. (2024) demonstrated that routinely available maternal characteristics could be used to develop ML models with useful predictive performance. Their findings showed that Random Forest achieved stronger discrimination than conventional Logistic Regression in their dataset. Importantly, the study identified clinically recognizable variables—including previous preeclampsia, BMI, maternal age, hypertension, diabetes, and blood pressure—as important predictors.

Recent systematic reviews have further supported the potential of ML while simultaneously highlighting concerns regarding generalizability. Malik et al. (2024) found that ML-based prediction models for preeclampsia generally demonstrated promising discrimination but varied considerably in methodology and predictor selection. Özcan and Peker (2025) similarly identified Random Forest, Support Vector Machine, Logistic Regression, and XGBoost among commonly evaluated algorithms. However, much of the available evidence originates from high-income or technologically advanced healthcare systems, limiting its direct applicability to Pakistan.

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A major methodological concern is that strong internal predictive performance does not necessarily indicate clinical usefulness. Dkeen et al. (2025) reported promising discrimination among ML models for obstetric risk prediction but identified limited external validation as a persistent weakness. More recent evidence has reinforced this concern. Liu et al. (2026) found high pooled predictive performance for ML-based preeclampsia models but substantial heterogeneity and relatively limited external validation. These findings demonstrate the importance of population-specific model development and independent validation before ML systems are integrated into clinical practice.

Another important gap concerns the outcome itself. Much of the existing literature predicts the development of preeclampsia generally rather than severe preeclampsia specifically. These outcomes are related but clinically distinct. A prediction model designed specifically to identify women at risk of severe disease may be more relevant for early referral, intensified surveillance, and prevention of catastrophic maternal and fetal complications.

The choice of predictors is also important in the Pakistani context. Models based on expensive biomarkers or highly specialized investigations may demonstrate excellent performance but have limited feasibility in primary and secondary healthcare facilities. A model based predominantly on routinely available EHR variables—including maternal age, BMI, parity, previous preeclampsia, blood pressure, diabetes, chronic hypertension, and selected laboratory measurements—may offer greater scalability.

Longitudinal information may provide additional predictive value. Wu et al. (2022) demonstrated that modelling pregnancy trajectories from routinely collected EHR data could improve preeclampsia risk prediction. Similarly, Ballard et al. (2024) demonstrated the feasibility of predicting preeclampsia onset using a limited number of EHR-derived features. These findings support the use of repeated clinical observations rather than relying exclusively on a single antenatal assessment.

Despite the growing evidence, there remains a significant gap in population-specific ML research addressing severe preeclampsia in Pakistan. The absence of validated local prediction models limits the ability of healthcare providers to determine whether models developed in other populations can be reliably transferred to Pakistani women. Differences in maternal characteristics, disease prevalence, healthcare access, clinical documentation, and referral systems may substantially influence model performance.

Therefore, this study proposes an ML-based framework for the early prediction of severe preeclampsia using electronic maternal health records in Pakistan. The study focuses on routinely available maternal and clinical variables and evaluates the predictive potential of ML algorithms while emphasizing interpretability and clinical relevance. By developing a population-specific predictive framework, the study aims to contribute evidence toward more proactive, data-driven maternal healthcare in Pakistan.

## 2. Problem Statement

Preeclampsia continues to pose a substantial challenge to maternal healthcare because of its heterogeneous presentation, unpredictable progression, and potential to cause severe maternal and fetal complications. Although conventional clinical risk assessment provides important information, it may not sufficiently capture the complex interactions among demographic, obstetric, physiological, and laboratory characteristics that precede severe disease. Consequently, some women who subsequently develop severe preeclampsia may not be identified early enough to receive intensified monitoring or timely referral.

The challenge is particularly significant in Pakistan, where maternal healthcare delivery is characterized by disparities in accessibility, continuity of antenatal care, diagnostic capacity, and specialist referral. Evidence from Pakistan and other low-resource settings indicates that delays in recognizing and managing pregnancy-related hypertensive disorders can contribute to preventable maternal morbidity and mortality (von Dadelszen et al., 2020). A reliable early

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prediction mechanism could therefore have considerable clinical and public-health relevance.

Although ML has increasingly been applied to preeclampsia prediction, important gaps remain. First, existing research is geographically concentrated in populations outside South Asia, and relatively limited evidence is available from Pakistan. Models trained using foreign populations may not perform equivalently in Pakistani women because differences in demographic composition, nutritional status, comorbidities, healthcare utilization, diagnostic practices, and disease prevalence can influence predictive relationships.

Second, much of the literature focuses on predicting preeclampsia as a general outcome rather than severe preeclampsia. This distinction is clinically important because severe disease is associated with substantially greater risk and requires more urgent clinical decision-making.

Third, several existing models rely on specialized biomarkers, genetic information, or advanced investigations that may not be routinely available throughout Pakistan. While such variables may enhance prediction, their limited accessibility can restrict practical implementation. There is therefore a need for prediction models based primarily on routinely collected electronic maternal health information.

Fourth, the methodological quality and generalizability of existing ML models remain concerns. Recent systematic reviews have reported high AUC values but substantial heterogeneity, inconsistent predictor selection, inadequate calibration reporting, and limited external validation (Dkeen et al., 2025; Liu et al., 2026). Thus, an apparently accurate model may perform poorly when transferred to a different hospital or population.

Fifth, the interpretability of ML models represents an additional challenge. Clinical adoption requires healthcare professionals to understand the principal factors underlying a prediction. A highly complex model that produces a risk score without an interpretable rationale may have limited acceptance, particularly when its output could influence referral or treatment decisions.

Accordingly, the central research problem is the lack of a population-specific, interpretable, and clinically relevant ML framework for early prediction of severe preeclampsia using routinely available electronic maternal health records in Pakistan. Addressing this problem requires the integration of established maternal risk factors with EHR-derived clinical information and systematic evaluation of alternative ML algorithms.

This study therefore seeks to determine whether ML can provide accurate early prediction of severe preeclampsia in Pakistani pregnant women and whether such models can offer useful information beyond conventional statistical prediction. The research also seeks to identify the most influential predictors and establish a foundation for future multicenter external validation and clinical implementation.

## 3. Research Questions

1. Which demographic, obstetric, clinical, and laboratory variables are associated with severe preeclampsia among pregnant women in Pakistan?
2. How accurately can electronic maternal health records be used to predict severe preeclampsia through ML?
3. Which ML algorithm provides the highest predictive performance for severe preeclampsia?
4. Which maternal and clinical characteristics contribute most strongly to the prediction of severe preeclampsia?
5. Does ML provide better predictive performance than conventional Logistic Regression?
6. How suitable is the resulting prediction framework for future clinical validation and implementation in Pakistani healthcare settings?

## 4. Research Objectives

### General Objective

To develop and evaluate a machine-learning-based model for the early prediction of severe preeclampsia using electronic maternal health records in Pakistan.

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**Specific Objectives**

1. To identify demographic, obstetric, clinical, and laboratory variables associated with severe preeclampsia.
2. To develop ML models for the early prediction of severe preeclampsia using routinely available electronic maternal health data.
3. To compare the predictive performance of Logistic Regression, Random Forest, Support Vector Machine, and XGBoost.
4. To evaluate the models using AUC, sensitivity, specificity, precision, F1-score, and calibration.
5. To identify the most influential predictors of severe preeclampsia using explainable ML techniques.
6. To determine whether ML models provide superior predictive performance compared with conventional Logistic Regression.
7. To establish an interpretable predictive framework suitable for future multicenter validation in Pakistan.

## 5. Significance of the Study

### 5.1 Theoretical Significance

The study contributes to the emerging intersection of maternal epidemiology, predictive analytics, and artificial intelligence. It extends conventional risk-prediction approaches by examining whether nonlinear and interactive relationships among maternal characteristics can improve prediction of severe preeclampsia. The study also contributes population-specific evidence from Pakistan, an underrepresented setting in the ML-based maternal-health literature.

### 5.2 Clinical Significance

Early identification of women at high risk of severe preeclampsia could enable clinicians to intensify antenatal surveillance, repeat relevant investigations, initiate appropriate preventive or therapeutic measures, and arrange timely referral to higher-level obstetric care. The proposed model would function as a clinical decision-support tool rather than a replacement for professional medical judgment.

### 5.3 Practical Significance

A major practical contribution is the emphasis on routinely available electronic maternal health information. A model that can operate using commonly recorded variables may be more feasible for implementation in Pakistani hospitals than models dependent on expensive biomarkers or specialized diagnostic technologies.

### 5.4 Policy Significance

The findings could support policymakers in considering AI-enabled maternal-health surveillance within Pakistan's expanding digital-health infrastructure. A validated prediction system could potentially contribute to risk-based referral, resource allocation, and maternal-health monitoring. However, implementation should follow rigorous external validation, fairness assessment, data-security safeguards, and prospective evaluation.

### 5.5 Research Significance

The study provides a foundation for future multicenter research involving larger Pakistani populations. It can also facilitate subsequent investigation of longitudinal prediction, model fairness, explainable AI, biomarker integration, and real-world clinical effectiveness.

## Literature Review

Recent research demonstrates growing interest in machine learning (ML) for early prediction of preeclampsia using electronic health records (EHRs). Traditional prediction approaches primarily rely on predefined risk factors such as maternal age, obesity, previous preeclampsia, chronic hypertension, diabetes, and parity. Although clinically useful, these approaches may inadequately capture nonlinear relationships and interactions among multiple maternal characteristics (Phipps et al., 2019).

Recent systematic reviews indicate that ML models generally demonstrate promising predictive performance. Ranjbar et al. (2024) reported AUC values ranging from 0.860 to 0.973 across reviewed ML models, with Random Forest, XGBoost, and other ensemble approaches showing strong performance. Similarly, Malik et

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al. (2024) found that ML models achieved promising discrimination but emphasized methodological heterogeneity and limited external validation.

Evidence based on routinely collected clinical data is particularly relevant to Pakistan. Tiruneh et al. (2024) demonstrated that variables such as previous preeclampsia, BMI, maternal age, hypertension, diabetes, and blood-pressure measures could provide useful predictive information. Ballard et al. (2024) further demonstrated the potential of EHR-derived variables for predicting the timing of preeclampsia onset, supporting the value of longitudinal maternal records.

However, important research gaps remain. Özcan and Peker (2025) identified considerable geographical concentration of existing studies, while Dkeen et al. (2025) highlighted limited external validation. More recent evidence by Liu et al. (2026) showed that although ML models achieved high pooled discrimination, substantial heterogeneity and inadequate external validation limited their generalizability. Furthermore, most studies predict preeclampsia broadly rather than severe preeclampsia specifically.

Overall, the literature supports ML as a promising approach but demonstrates a need for population-specific, interpretable, externally validated models using routinely available data. This study addresses this gap by focusing specifically on early prediction of severe preeclampsia among Pakistani women using electronic maternal health records.

## Underpinning Theory

### Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) developed by Davis (1989) provides a suitable theoretical foundation for this study. TAM proposes that perceived usefulness **and** perceived ease of use influence users' acceptance of technology.

In this study, the ML prediction model represents a clinical decision-support technology. Its predictive accuracy and clinical utility contribute to perceived usefulness, while interpretability and transparency contribute to perceived ease of understanding and use. This is particularly important because clinicians are more likely to trust and incorporate an AI-based prediction system when they can understand the factors contributing to its risk assessment.

TAM is therefore applicable because the study is not limited to developing an accurate algorithm; it also seeks to develop an interpretable and clinically relevant prediction framework that could eventually be integrated into maternal healthcare practice in Pakistan. Davis's (1989) framework consequently provides a theoretical basis for linking ML performance and interpretability with potential clinical adoption.

## Hypotheses

**H1:** Higher maternal blood-pressure levels are positively associated with the predicted risk of severe preeclampsia.

**H2:** Previous history of preeclampsia is positively associated with the predicted risk of severe preeclampsia.

**H3:** Higher maternal BMI is positively associated with the predicted risk of severe preeclampsia.

**H4:** Chronic hypertension is positively associated with the predicted risk of severe preeclampsia.

**H5:** Maternal diabetes is positively associated with the predicted risk of severe preeclampsia.

**H6:** Machine learning models demonstrate significantly greater predictive performance than conventional Logistic Regression.

## Methodology

### Research Design

A retrospective quantitative cohort design was employed to develop and evaluate machine-learning models for the early prediction of severe preeclampsia using electronic maternal health records.

### Population

The population comprised pregnant women receiving antenatal care in selected public and private hospitals in Pakistan. For analysis, records of 1,000 pregnant women were considered, including 120 women (12.0%) diagnosed with severe preeclampsia and 880 without severe preeclampsia.

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**Sampling Technique**

**Consecutive sampling** was employed. All eligible electronic maternal records meeting the inclusion criteria during the specified study period were considered until the sample of 1,000 records was obtained.

**Sample Size**

A sample of 1,000 maternal records was used. The dataset contained 880 non-severe cases and 120 severe-preeclampsia cases, providing sufficient outcome variation for demonstrating predictive modelling procedures.

**Data Collection Procedures**

De-identified maternal records were extracted from electronic hospital information systems using a standardized data-extraction template. Information recorded before the predefined prediction point was retained to prevent data leakage**.** The dataset included demographic, obstetric, clinical, and laboratory variables.

**Instruments and Measures**

The electronic health record extraction template included:

- Maternal age (years)
- BMI (kg/m²)
- Gravidity and parity
- Previous preeclampsia (yes/no)
- Chronic hypertension (yes/no)
- Diabetes mellitus (yes/no)
- Gestational age (weeks)
- Systolic and diastolic blood pressure (mmHg)
- Mean arterial pressure (mmHg)
- Proteinuria
- Platelet count
- Serum creatinine
- AST and ALT
- Severe preeclampsia status (0 = No, 1 = Yes)

Severe preeclampsia was classified according to established clinical diagnostic criteria.

**Reliability and Validity**

Data reliability was enhanced through a standardized extraction protocol, duplicate checking, range validation, and consistent variable coding**.** Construct validity was supported by selecting predictors established in previous preeclampsia research. Criterion validity was assessed by comparing model predictions with documented clinical outcomes. Internal validity was strengthened through appropriate preprocessing, cross-validation, and separation of training and testing datasets. Model generalizability was assessed through independent testing and was recommended for further external validation using data from other Pakistani hospitals**.**

**Data Analysis**

The dataset consisted of **1,000 maternal records**, including 120 (12.0%) women with severe preeclampsia and 880 (88.0%) without severe preeclampsia. Data were analyzed using descriptive statistics, inferential analysis, and machine-learning classification. Logistic Regression, Random Forest, Support Vector Machine (SVM), and XGBoost were compared using accuracy, sensitivity, specificity, F1-score, and area under the receiver operating characteristic curve (AUC-ROC). The results below are synthetic findings intended to demonstrate the presentation of an empirical study.

**Table 1 Descriptive Characteristics of the Study Population**

| Variable | No Severe Preeclampsia (n=880) | Severe Preeclampsia (n=120) | Total (N=1,000) |
|---|---|---|---|
| Maternal age, years (M ± SD) | 27.8 ± 5.1 | 31.2 ± 5.7 | 28.2 ± 5.3 |
| BMI, kg/m² (M ± SD) | 25.8 ± 4.1 | 29.1 ± 4.8 | 26.2 ± 4.3 |
| Previous preeclampsia, n (%) | 71 (8.1) | 38 (31.7) | 109 (10.9) |
| Chronic hypertension, n (%) | 53 (6.0) | 29 (24.2) | 82 (8.2) |

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| Variable | No Severe Preeclampsia (n=880) | Severe Preeclampsia (n=120) | Total (N=1,000) |
|---|---|---|---|
| Diabetes, n (%) | 74 (8.4) | 24 (20.0) | 98 (9.8) |
| Systolic BP, mmHg (M ± SD) | 123.6 ± 12.7 | 146.8 ± 17.1 | 126.4 ± 15.0 |
| Diastolic BP, mmHg (M ± SD) | 78.2 ± 8.6 | 94.7 ± 11.5 | 80.2 ± 10.0 |
| Mean arterial pressure, mmHg (M ± SD) | 93.3 ± 8.7 | 112.1 ± 11.8 | 95.6 ± 10.5 |

The descriptive findings indicate substantial differences between women with and without severe preeclampsia. Women who developed severe preeclampsia were, on average, older and had higher BMI. Previous preeclampsia was observed in 31.7% of severe cases compared with only 8.1% of non-severe cases. Chronic hypertension and diabetes were also considerably more prevalent among severe cases. Most notably, systolic blood pressure, diastolic blood pressure, and mean arterial pressure were substantially higher among women who developed severe disease. These patterns are consistent with established clinical evidence identifying previous preeclampsia, hypertension, metabolic factors, and elevated blood pressure as important risk indicators.

**Table 2 Logistic Regression Analysis**

| Predictor | Adjusted OR | 95% CI | p-value |
|---|---|---|---|
| Maternal age | 1.08 | 1.04–1.12 | <.001 |
| BMI | 1.12 | 1.07–1.17 | <.001 |
| Previous preeclampsia | 3.46 | 2.05–5.84 | <.001 |
| Chronic hypertension | 3.18 | 1.79–5.65 | <.001 |
| Diabetes | 2.21 | 1.30–3.76 | .003 |
| Systolic BP | 1.07 | 1.05–1.09 | <.001 |
| Diastolic BP | 1.05 | 1.02–1.08 | <.001 |

The regression analysis indicates that all examined predictors were positively associated with severe preeclampsia. Previous preeclampsia demonstrated the strongest categorical association, with women having a previous history showing approximately 3.46 times greater odds of severe disease. Chronic hypertension and diabetes were also associated with substantially increased odds. Maternal age and BMI showed positive associations, while both systolic and diastolic blood pressure demonstrated significant increases in risk. These findings suggest that severe preeclampsia is associated with a combination of historical, metabolic, and current physiological characteristics rather than a single determinant.

**Table 3 Machine-Learning Model Performance**

| Model | AUC | Accuracy | Sensitivity | Specificity | F1-Score |
|---|---|---|---|---|---|
| Logistic Regression | 0.82 | 0.81 | 0.75 | 0.82 | 0.61 |
| Random Forest | 0.89 | 0.86 | 0.83 | 0.87 | 0.68 |
| SVM | 0.86 | 0.84 | 0.79 | 0.85 | 0.65 |

| Model | AUC | Accuracy | Sensitivity | Specificity | F1-Score |
|---|---|---|---|---|---|
| XGBoost | **0.91** | **0.88** | **0.86** | **0.89** | **0.72** |

The ML comparison indicates that XGBoost produced the strongest overall predictive performance, with an AUC of 0.91, followed by Random Forest (AUC = 0.89), SVM (AUC = 0.86), and Logistic Regression (AUC = 0.82). XGBoost also demonstrated the highest sensitivity and specificity, suggesting better identification of women who subsequently developed severe preeclampsia while maintaining acceptable classification of non-cases.

The difference between Logistic Regression and the ensemble-based algorithms suggests that nonlinear relationships and interactions among predictors may contain additional predictive information. Nevertheless, the relatively strong performance of Logistic Regression indicates that conventional statistical modelling remains clinically relevant and provides an interpretable benchmark.

**Table 4 Feature-Importance Ranking for the Best-Performing Model**

| Rank | Predictor | Relative Importance |
|---|---|---|
| 1 | Systolic blood pressure | 0.184 |
| 2 | Mean arterial pressure | 0.161 |
| 3 | Previous preeclampsia | 0.145 |
| 4 | Diastolic blood pressure | 0.119 |
| 5 | BMI | 0.097 |
| 6 | Chronic hypertension | 0.083 |
| 7 | Maternal age | 0.071 |
| 8 | Diabetes | 0.058 |
| 9 | Gestational age | 0.044 |
| 10 | Parity | 0.038 |

Blood-pressure-related variables were the most influential predictors in the XGBoost model, followed by previous preeclampsia and BMI. This finding indicates that current maternal physiological status and previous obstetric history contributed substantially to risk classification. The importance of previous preeclampsia is clinically plausible because recurrence represents an established risk factor. Similarly, chronic hypertension and diabetes may increase susceptibility through vascular and metabolic pathways.

The feature-importance results should not, however, be interpreted as evidence of causality. A variable may be highly useful for prediction without being a direct causal determinant of disease. Explainable ML methods such as SHAP can provide additional patient-level interpretation by showing whether individual predictor values increase or decrease the predicted risk.

**Table 5 Confusion Matrix for XGBoost**

| | Predicted No Severe PE | Predicted Severe PE |
|---|---|---|
| Actual No Severe PE | 783 | 97 |
| Actual Severe PE | 17 | 103 |

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The confusion matrix indicates that the model correctly identified **103 of 120 severe cases**, producing a sensitivity of approximately **85.8%**. It correctly classified 783 of 880 non-severe cases, corresponding to a specificity of approximately **89.0%**.

**Overall Interpretation**

Taken together, the findings suggest that ML can provide meaningful predictive value for severe preeclampsia using routinely available maternal health information. XGBoost demonstrated the strongest discrimination, while Random Forest also performed well. The superior performance of these ensemble models over Logistic Regression may indicate that complex nonlinear relationships among blood pressure, previous obstetric history, BMI, hypertension, diabetes, and maternal characteristics contribute to severe-preeclampsia risk.

The findings are broadly consistent with recent research reporting promising performance of ML approaches for preeclampsia prediction (Ranjbar et al., 2024; Tiruneh et al., 2024; Malik et al., 2024). However, the results must not be interpreted as actual clinical evidence from Pakistan. Before publication, the tables should be regenerated from the actual dataset, accompanied by confidence intervals, statistical significance testing, calibration analysis, and preferably external validation.

For a clinically oriented model, sensitivity should receive particular attention, because incorrectly classifying a woman who subsequently develops severe preeclampsia may have substantially greater clinical consequences than incorrectly classifying a low-risk woman as high risk.

**Discussion**

The findings indicate that **XGBoost (AUC = 0.91)** demonstrated the strongest predictive performance, followed by Random Forest (0.89), SVM (0.86), and Logistic Regression (0.82). This pattern is broadly consistent with recent evidence reporting strong performance from ensemble ML models in preeclampsia prediction (Ranjbar et al., 2024; Tiruneh et al., 2024; Malik et al., 2024). The importance of blood pressure, previous preeclampsia, BMI, hypertension, and diabetes also corresponds with previously identified clinical predictors.

However, recent systematic evidence cautions that high internal predictive performance does not necessarily ensure external validity. Liu et al. (2026) reported substantial heterogeneity among ML prediction studies and limited external validation. Therefore, the present findings should be interpreted as preliminary evidence requiring validation across independent Pakistani populations.

From a theoretical perspective, the findings support the Technology Acceptance Model (TAM) because a clinically useful ML system requires both perceived usefulness and ease of understanding. The strong predictive performance provides potential usefulness, while feature-importance analysis can improve interpretability and clinician confidence.

**Conclusion**

The findings suggest that machine learning, particularly XGBoost and Random Forest, can potentially improve early prediction of severe preeclampsia using routinely collected electronic maternal health information. Blood pressure, previous preeclampsia, BMI, hypertension, and diabetes emerged as important predictors. A validated and interpretable ML model could support earlier risk identification and clinical decision-making in Pakistan. Nevertheless, the results require confirmation using actual patient data and independent external validation.

**Implications**

**Theoretical:** The study extends predictive-health research by integrating ML with clinical risk assessment and TAM.

**Managerial:** Healthcare managers could use validated prediction systems to improve maternal-risk monitoring, referral prioritization, and resource allocation.

**Practical:** Clinicians could use risk predictions to support intensified surveillance and timely referral while retaining professional clinical judgment.

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**Policy:** Health authorities could consider integrating validated ML prediction tools into digital maternal-health systems, subject to ethical, privacy, fairness, and validation requirements.

**Recommendations**

1. Develop ML models using standardized electronic maternal health records.
2. Prioritize routinely available predictors to improve implementation feasibility.
3. Conduct multicenter and external validation across Pakistan.
4. Evaluate calibration and clinical utility in addition to AUC.
5. Incorporate explainable AI to improve clinical transparency.
6. Conduct prospective studies to determine whether ML-supported prediction improves maternal and neonatal outcomes.
7. Establish appropriate data-governance, privacy, and algorithmic-fairness standards before clinical deployment.

**Limitations and Future Directions**

The principal limitation is that the reported findings are and based on synthetic sample data**,** not actual patient records. Consequently, the reported performance metrics cannot be interpreted as genuine clinical evidence. A retrospective EHR design may also be affected by missing data, inconsistent documentation, selection bias, and institutional differences. Class imbalance and limited representativeness may further affect model performance.

Future research should use large multicenter Pakistani datasets**,** conduct temporal and external validation, assess algorithmic fairness and calibration, incorporate longitudinal measurements, and evaluate the clinical impact of ML-assisted risk stratification through prospective studies.

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